Socially-accepted Path-planning for Autonomous Robot Navigation based on Social Interaction Spaces

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***Abstract*— Path planning is one of the most widely studied problems in robot navigation. It deals with estimating an optimal set of waypoints from an initial to a target coordinate. New generations of assistive robots should be able to compute these paths considering not only obstacles but also social conventions. This ability is commonly referred to as social navigation. This paper describes a new socially-acceptable path-planning framework where robots avoid entering areas corresponding to the personal spaces of people, but most importantly, areas related to human-human and human-object interaction. To estimate the social cost of invading personal spaces we use the concept of proxemics. To model the social cost of invading areas where interaction is happening we include the concept of object interaction space. The framework uses Dijkstra's algorithm on a uniform graph of free space where edges are weighed according to the social traversal cost of their outbound node. Experimental results demonstrate the validity of the proposal to plan socially-accepted paths.**

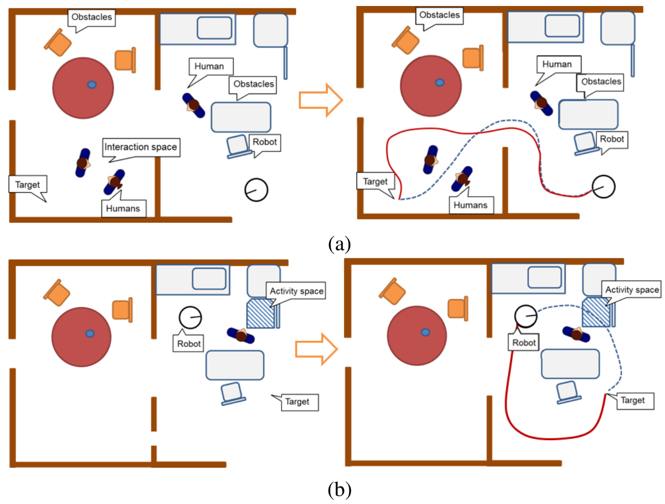

Fig. 1: Two different everyday scenarios: a) left: original scenario where two people are interacting each other (interaction space); right: red path is the only one accepted by people according to social conventions; and b) left: the interaction between the human and the fridge blocks the path; right: red path is socially-accepted.

I. Introduction

The interest that research in social robotics has drawn in the last decade is remarkable, especially in human-populated environments such as museums and hospitals. Working in these scenarios is challenging, as people's behaviour changes frequently and their state is difficult to predict over time. To make these robots able to work seamlessly in these environments, they must act considering social conventions, including those related to navigation.

Traditionally, navigation has been approached by solving three main problems: i) where is the robot in the world, that is, the localization problem; ii) how the world around the robot is and how it is built; and iii) how robot plans an optimal path, which is usually known as the path-planning problem. All these problems have been arousing interest for decades, and many solutions have been presented in simple as well as complex environments. However, in human environments, it is more difficult and novel to find optimal solutions. This is the particular case of algorithms that plan socially-accepted paths for robots.

Social navigation is expected to become an increasingly important skill in the next generation of social robots [1]. During recent years many works have been proposed to make robot navigation algorithms consider social aspects [2]. Fig. 1 shows two different scenarios where the robot plans a path to the target in environments with people. In Fig. 1a, the robot has several options to reach the destination, but only one is is the most accepted (highlighted in red). Similarly, Fig. 1b shows another scenario where robot has different possible routes, but only one is the most appropriate in social terms (also illustrated in red).

To estimate the best social route from the robot to the target pose, this work proposes using the concept of social mapping [3]. Unlike classical path planning approaches, the proposal described in this paper adds social information on top of the free-space graph previously built in order to build a social map. To this end, the system associates different personal spaces (intimate, social and public) to humans and groups of people in the environment. In the same way, the algorithm associates different activity spaces to objects with which people can interact (known as *Space Affordances* [4]). These different interaction spaces modify the free space graph, penalizing the cost of traversing some areas when planning the path to the target [5].

The **main contributions** of this paper are: i) the definition of a new framework for planning social paths in human and interactive environments; ii) the description of a novel social path-planning algorithm based on social interaction spaces that uses information from people and objects; iii)

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an adaptive methodology to penalize paths depending of the level of confidence between the robot and people.

This paper is organized as follows: Section II provides a discussion of previous works related to robot navigation in environment with people. Section III presents an overview of the proposed social navigation architecture, including the definition of the social interaction spaces. Section IV describes the socially-accepted path-planning algorithm presented in this paper. In Section V, the experimental results are outlined. The conclusions and future works of the approach are summarized in Section VI.

II. Related work

Path-planning in human environments is a complex problem that has aroused great interest in recent years. The way in which a robot navigates in these environments must not only consider task constraints, such as minimizing the distance traveled to the target, but also social rules, such as keeping a comfortable distance from humans [6]. Most works use proxemics (*i.e.*, the relationship between distances and the type of interaction) in order to plan a socially-accepted path [3], [7], [8]. These works typically define regions in which robot's navigation is forbidden. Other authors use the term affordances of objects and/or activity spaces, and try to prevent robots from navigating near them creating regions where navigation is forbidden [4], [9]. The definition of these regions that allow a more social navigation is what is usually called *social mapping*, which extends classical concepts such as *metric and/or semantic mapping* by defining these social interaction spaces. The proposal described in this paper uses a framework to perceive social interaction spaces and build a social map of the environment.

Classical methods need global path planners in order to choose the best route from the robot to the target and then, they apply social conventions and constraints to modify this path. Classical global path planners use a spatial representation of the robots surrounding, so they require a map of the environment. Numerous path-planning algorithms have been proposed in the literature, from classical Dijkstra or A* algorithms to other more complex systems. An interesting review of path planning algorithms was written by LaValle et al. [14].

How autonomous robots move in human environments has a strongly effect on the perceived intelligence [10]. A path that explicitly takes into account the human presence in the environment must address situations such as not passing between two people talking or avoid getting out of the field of view of the people, with the possibility of scaring them unnecessarily. Social navigation started being extensively studied in the last years and several methods have been proposed since then. On one hand, some authors propose models of social rules by using cost functions [11], [12]. A typical solution is to add social conventions and/or social constraints. In [11], for instance, the authors use a classical A* path planner in conjunction with social conventions, like to pass a person on the right. Other work such as [12] use potential fields and a proxemics model. On the other hand,

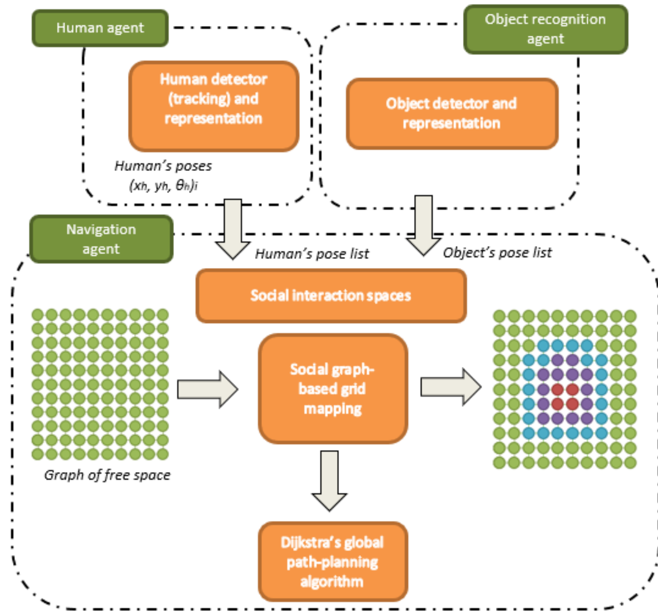


Fig. 2: Overview of the proposal.

several authors use human intentions in order to model the social navigation [13]. Recently, in the work presented in [6], the concept of interaction spaces and their use to define social paths is introduced. This same concept is described in this article, but also adding the spaces of interaction between people and objects in the environment. The proposal uses the classical Dijkstra's algorithm, where weights of the graphs are modified in order to take into account the social map of the environment.

III. Social interaction spaces in real environments

This section describes the framework for planning socially-acceptable paths in human and interactive environments. In order to compute paths in these real scenarios, it is necessary to create a social map of the environment. For this reason, the robot's perception system needs to: i) detect and model people (position and orientation); ii) model their social space of interaction; iii) group people in case they are engaged in interaction, modelling the space they need to do such interaction; and iv) detect objects and model their space of interaction according to their *Space Affordances*. Fig. 2 shows an outline of the proposed system. The proposed framework uses the CORTEX cognitive architecture for communication between perception agents and the robot navigation system (see [16] for a detailed description of the architecture). Next, the framework is described in details.

A. Social spaces of interaction

The proposal for human-aware social navigation uses the model described in [4]. In this model, the presence of people generate regions where navigation is forbidden or penalized. Let $H_n = \{h_1, h_2...h_n\}$ be a set of n humans detected by the people perception system, where $h_i = (x, y, \theta)$ is the pose of the i-th human in the environment[1]. To model the personal space of each individual h_i an asymmetric 2-D Gaussian curve $g_i(x, y)$ is used [4]:

$$g_{h_i}(x, y) = e^{-(k_1(x-x_i)^2+k_2(x-x_i)(y-y_i)+k_3(y-y_i)^2)} \quad (1)$$

being k_1, k_2 and k_3 the coefficients used to take into account the rotation of the function β_i, defined by the relations

$$\begin{aligned} k_1(\beta_i) &= \frac{cos(\beta_i)^2}{2\sigma^2} + \frac{sin(\beta_i)^2}{2\sigma_s^2} \\ k_2(\beta_i) &= \frac{sin(2\beta_i)}{4\sigma^2} - \frac{sin(2\beta_i)}{4\sigma_s^2} \\ k_3(\beta_i) &= \frac{sin(\beta_i)^2}{2\sigma^2} + \frac{cos(\beta_i)^2}{2\sigma_s^2} \end{aligned}$$

where σ_s is the variance on the left and right ($\beta_i \pm \pi/2$ direction) and defines the variance along the β_i direction (σ_h), or the variance to the rear (σ_r) (see [4]). In Fig. 3 an example of the personal space model, as an asymmetric Gaussian, is shown (labeled as '1' in Fig. 3b).

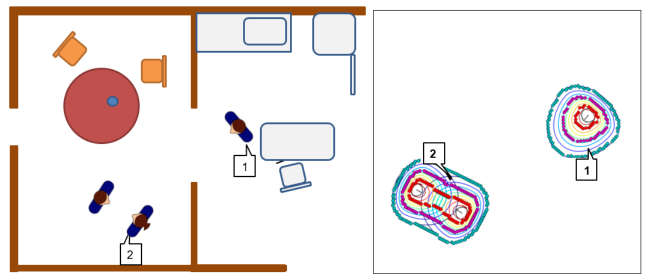
Once people have been detected, the algorithm clusters humans in the environment according their distances by performing a Gaussian Mixture, as described in [4]. The personal space function $g_i(h)$ of each individual i in the environment is summed and a Global Space function $G(p)$ is built. From this function, a contour J_i is established as a function of the density threshold ϕ. Finally, the contours of these forbidden regions are defined by a set of k polygonal chain ($i.e.$, polyline) $L_k = \{l_1, ..., l_k\}$, where k is the number of regions detected by the algorithm. The curve l_i is described as $l_i = \{a_1, ..., a_m\}$, being $a_i = (x, y)_i$ the vertices of the curve, which are located in the contour of the region J.

According to [8] it is possible to classify the space around a person into four zones, depending on social interaction: public, social, personal and intimate zones. Each human h_i present in the environment will have three associated spaces: the intimate space, defined by the polyline $L_k{}^{intimate}$; the personal space, defined by $L_k{}^{personal}$; and the social space, delimited by $L_k{}^{social}$, each of them being larger than the previous one, as it was introduced in [8]. The public zone will be the remaining free space. These contours, which are created by choosing different values of the density threshold ϕ, can be seen in the Fig. 3: in color red is shown the intimate space, in purple the personal one and as blue color the social space.

B. Space Affordances and Activity Spaces

The concept of *Space Affordances* refers to areas where humans usually perform particular activities [9]. In interactive scenarios, these spaces are related to objects with which people often interact, for example, the space near a poster or a coffee machine. These spaces are called *Activity spaces* when people interact with objects.

[1]The actual detection of humans is out of the scope of the paper. In the experiments carried out it was performed by the Human agent of the CORTEX architecture.



(a) (b)

Fig. 3: a) People in a simulated environment; b) asymmetric Gaussian associated to person '1' and clustering of the group of two people labeled as '2' in Fig. 3a.

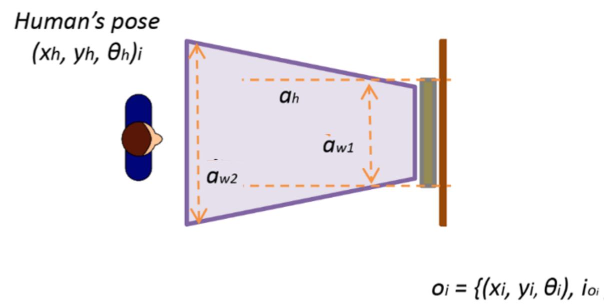


Fig. 4: Social interaction modeling: the Space Affordance of an interactive object is modeled by a symmetrical trapezoid.

Let $O_n = \{o_1, ..., o_n\}$ be the set of n objects with which humans interact in the environment. Each object o_k stores the interaction space i_{o_k} as an attribute, which is associated to the space required to interact with this object, and also its pose $p_{o_k} = (x, y, \theta_k)$,

$$o_k = (p_{o_k}, i_{o_k})$$

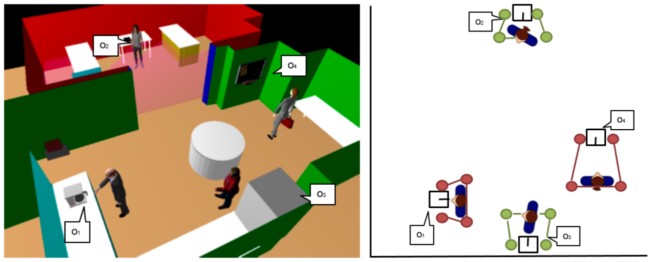
Different objects in the environments have different interaction spaces. For instance, when using a coffee machine, a smaller space is needed in comparison to when reading a poster because it can be done from a farther distance.

Next, the *Space Affordance* A_{o_k} is defined for each object $o_k \in O_n$. In this paper, the shape of these spaces has been modeled as an symmetrical trapezoid with height a_h and widths (a_{w1}, a_{w2}), as shown in Fig. 4, being a_{w2} defined as in the following equation:

$$a_{w2} = (a_{w1} \cdot a_h)/4$$

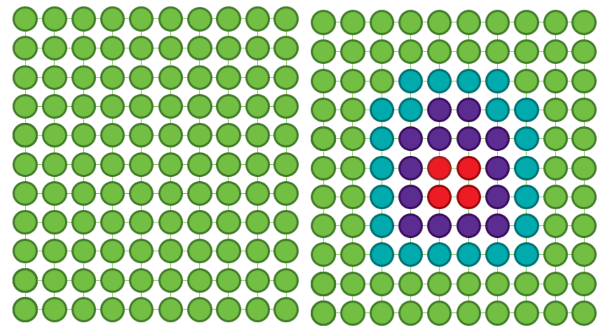
Once the *Space Affordances* A_{o_k} is built, it is checked if it is actually being used as an *Activity Space*. Two constraints have to be fulfilled to consider that an activity is being carried used: the person h_i has to be inside the *Space Affordance* and has to be looking at the object o_k.

The space will be forbidden for navigation if these conditions are true. Thus, A_{o_k} is modeled by a polyline described by four vertices v_a that will be used to delimit forbidden



(a) (b)

Fig. 5: Examples of social interaction spaces: a) People interacting with different objects in the environment; and b) the corresponding space affordances representation generated by the algorithm.



(a) (b)

Fig. 6: Graph-based grid mapping: a) original free-space graph; and b) final free-space graph, after including the social interaction space associated to a person.

areas for navigation. Finally, the set $L_o = \{A_{o_1}, ..., A_{o_n}\}$ describes the set of polylines used by the navigation algorithm for defining forbidden navigation areas.

In Fig. 5a four humans in different poses and four objects are shown (a coffee machine, a fridge, a phone, and a pin board). Some of the humans are interacting with the objects. The position of the humans, the objects and the shapes of the spaces created for these objects are shown in Fig. 5b. The vertices v_a are shown in green if the space is being considered as free. These vertices are in green even if the person is inside the space but is not looking at the object. Red color means that the person is inside the *Space Affordance* and looking at the object (*i.e.*, the person is interacting with the object), so the space is being used as an activity space and, therefore, considered as occupied.

IV. Socially-acceptable path-planning algorithm

This section describes the social path-planning algorithm. The space is represented by a uniform graph where obstacle-free nodes have a constant finite traversal cost and non-free nodes have an infinite one. The proposed algorithm modifies the costs according to the social map previously built. This final graph is used to estimate the optimal path.

A. Graph-based grid mapping

Space is represented by a graph $G(N, E)$ of n nodes, regularly distributed in the environment. Each node n_i has two parameters: availability, a_n, and cost, c_n. The availability of a node is a boolean variable whose value is 1 if the space is free, 0 otherwise. The cost, c_i, indicates the traversal cost of a node, i.e., what it takes for the robot to visit that node. Initially, all nodes have the same cost 1. Fig. 6a shows an original free-space graph in which all nodes have the same cost and availability (as there are no obstacles in the area depicted).

The classical Dijkstra algorithm is employed for determining of the shortest path between an initial position and a target to which the robot must travel. Given a node of origin, the algorithm calculates the cost from origin to the target node taking into account the cost of the nodes. The cost of a path is the sum of the cost of the nodes that compose it.

B. Social graph-based grid mapping

The free space graph is modified to include the social spaces of interaction: firstly, those associated with the interaction between one person and another -or groups of people-, and secondly, those associated with the interaction between people and objects.

1) Personal Space mapping: Being A the matrix formed by the availability of each node of the free space graph and C the matrix formed by the costs and considering the set of polygonal curves defined bellow, $L_k{}^{intimate}$, $L_k{}^{personal}$ and $L_k{}^{social}$, this paper present the modification of the cost and availability of the nodes of the graph according to these interaction spaces.

In first place, considering only the intimate space around the person h_i, for each polyline $l_i^{intimate}$ is defined a polygon $P_i^{intimate}$ formed by the points of the polyline. The availability a_i of all the nodes $N_i \in N$ contained in the space formed by $P_o^{intimate}$ is set to occupied, $a_i = occupied$. This means that the robot will not be able to invade this space, as it would disturb the person. For personal and social spaces, the availability of the nodes of the graph will not be modified, but its cost will be changed.

Considering the personal space around the human h_i, for each polyline $l_i^{personal}$ a polygon $P_i^{personal}$ has been defined. The cost c_i of all the nodes $n_i \in N$, contained in the space formed by $P_p^{personal}$ will be modified and set to $c_i = 4.0$. In the same manner, for the social space, a polygon P_p^{social} is defined for each polyline $l_i^{personal}$. All the nodes $N_i \in N$ contained in the space formed by P_i^{social} will have cost $c_i = 2.0$. The public space will be the rest of the graph whose costs remain unchanged. Fig. 6b show the final free-space graph, where the costs of nodes are modified according to the social spaces of interaction.

Intimate areas forbidden for navigation. Personal and social spaces are available, but their costs are higher, being personal spaces more expensive than social spaces. This way, when the robot plans the shortest path, it will move away from the person. The social and personal spaces are not considered occupied so if the robot does not have enough space to navigate, for example in a corridor, it won't be blocked, but it will navigate through the social space, even if its cost is higher. If the robot does not have another alternative, it will cross the personal space, but it will never cross the intimate one.

2) Space Affordances of objects: This same technique has been used for *Space Affordances*. Let $L_o = \{A_{o_1}, ..., A_{o_n}\}$ be the set of polylines that describe the defined *Space Affordances*. For each A_{o_i} the polygon P_i^{aff} is formed. The nodes of the free space graph $N_i \in N$ contained in P_i^{aff} are modified in order to set its cost to $c_i = 1.5$. In this way, the *Space Affordances* have less weight in the graph than the social space of the person, so if the robot have to go through one of them, it will go through the *Space Affordance*.

V. Experimental Results

The software has been written in C++. The tests have been performed on a PC with an Intel Core i5 2.4GHz processor with 4Gb of DDR3 RAM and GNU/Linux Ubuntu 16.10.

In order to assess the effectiveness of the proposed navigation approach, the methodology has been evaluated accordingly to the following metrics: (i) average minimum distance to a human during navigation, d_{min}; (ii) distance traveled, d_t; (iii) navigation time, τ; (iv) cumulative heading changes, CHC; and (v) personal space intrusions, Ψ. These metrics have been already established by the scientific community (see [17], [18])

A. Navigation with interaction spaces

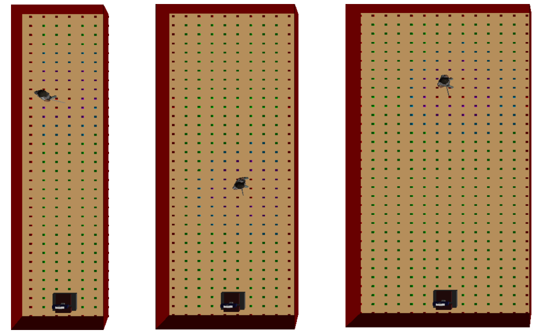
To evaluate the performance of the navigation algorithm, several simulations have been performed in three different environments rooms using a simulated robot. The widths of the rooms used were 2, 3 and $4m$. Fig. 7 depicts the used scenarios. The robot had to navigate from the position $x = 0m$, $y = 0m$ to $x = 8.5m$, $y = 0m$, through those scenarios in which a person was located in random positions. The aim of the experiment is to measure the percentage of time (i.e., the personal space intrusions, Psi) that the robot spends in each interaction space defined for the person, as explained in the section III-A.

The results obtained for the simulations of rooms 2, 3 and 4 meters wide can be found in the tables I, II and III, respectively.

B. Interactive scenario with Space Affordances

A rectangular simulated environment with a whiteboard has been used to test the effectiveness of the Space Affordance algorithm. The simulated environment is shown in Fig. 8a. The object has been placed in the position $x = 2m$, $y = 4.5m$ with $a_s = 3m$ in order to create a *Space Affordance* which the robot has to avoid, if it is being used as an *Activity Space*.

A single human, placed in front of the object in the position $x = 2m$, $y = 2m$, has been used for this test. The



(a) (b) (c)

Fig. 7: Scenarios used in the second experiment: a-c) 2m, 3m and 4m wides, respectively.

TABLE I: Navigation results for 2m wide room considering interaction spaces

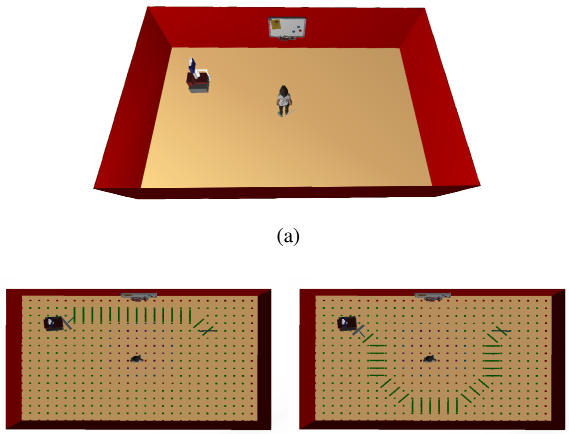
Navigation with Social Behaviour		Navigation without Social Behaviour	
Parameter	Obtained value (σ)	Parameter	Obtained value (σ)
d_t *(m)*	9.71 (0.56)	d_t *(m)*	9.10 (0.07)
τ*(s)*	40.39 (11.83)	τ*(s)*	35.54 (3.72)
CHC	1.49 (0.58)	*CHC*	0.79 (0.17)
d_{min} *Person (m)*	1.13 (0.16)	d_{min} *Person (m)*	0.47 (0.2)
Ψ *(Intimate) (%)*	0.0 (0.0)	Ψ *(Intimate) (%)*	1.58 (2.17)
Ψ *(Personal) (%)*	4.43 (7.38)	Ψ *(Personal) (%)*	5.55 (4.23)
Ψ *(Social) (%)*	16.46 (11.46)	Ψ *(Social) (%)*	17.26 (13.28)
Ψ *(Public) (%)*	79.10 (13.92)	Ψ *(Public) (%)*	75.60 (11.16)

TABLE II: Navigation results for 3m wide room considering interaction spaces

Navigation with Social Behaviour		Navigation without Social Behaviour	
Parameter	Obtained value (σ)	Parameter	Obtained value (σ)
d_t *(m)*	10.02 (0.49)	d_t *(m)*	9.50 (0.16)
τ*(s)*	31.39 (3.64)	τ*(s)*	29.95 (2.75)
CHC	0.88 (0.18)	*CHC*	0.68 (0.16)
d_{min} *Person (m)*	1.62 (0.28)	d_{min} *Person (m)*	0.70 (0.38)
Ψ *(Intimate) (%)*	0.0 (0.0)	Ψ *(Intimate) (%)*	1.06 (2.13)
Ψ *(Personal) (%)*	0.0 (0.0)	Ψ *(Personal) (%)*	8.15 (4.58)
Ψ *(Social) (%)*	3.29 (5.41)	Ψ *(Social) (%)*	14.95 (6.97)
Ψ *(Public) (%)*	96.70 (5.41)	Ψ *(Public) (%)*	75.83 (6.34)

TABLE III: Navigation results for 4m wide room considering interaction spaces

Parameter	Obtained value (σ)
d_t *(m)*	10.81 (0.55)
τ*(s)*	45.65 (19.24)
CHC	1.27 (0.51)
d_{min} *Person (m)*	1.76 (0.18)
Ψ *(Intimate) (%)*	0.0 (0.0)
Ψ *(Personal) (%)*	0.0 (0.0)
Ψ *(Social) (%)*	2.017 (3.37)
Ψ *(Public) (%)*	97.98 (3.37)



(a)

(b) (c)

Fig. 8: Interactive scenario described for the test and navigation results with and without *Space Affordances*: a) original scenario; b) Navigation without Space Affordance; and c) Navigation with Space Affordance

TABLE IV: Navigation results with space affordances

Navigation with space affordances		Navigation without space affordances	
Parameter	Value (σ)	Parameter	Value (σ)
d_t *(m)*	8.76m	d_t	5.18m
τ	64.1s	τ	33.84s
CHC	1.47 (0.11)	*CHC*	0.21 (0.05)
d_{min} *Person (m)*	0.78 (0.007)	d_{min} *Person (m)*	1.10 (0.005)
Ψ *(Intimate) (%)*	0.0 (0.0)	Ψ *(Intimate) (%)*	0.0 (0.0)
Ψ *(Personal)(%)*	0.0 (0.0)	Ψ *(Personal)(%)*	0 (0.0)
Ψ *(Social)(%)*	15.46 (0.6)	Ψ *(Social)(%)*	12.54 (0.57)
Ψ *(Public)(%)*	84.53 (0.6)	Ψ *(Public)(%)*	87.44 (0.9)
Interruption (Y/N)	N	*Interruption (Y/N)*	Y

robot has had to navigate from the position $x = -0.8m$, $y = 3m$ to $x = 4.5m$, $y = 3m$, avoiding the *Activity Space*.

The same test has been carried out with and without *Space Affordances*. The comparison between the different paths the robot took can be seen in Fig. 8b, and Fig. 8c where the paths planned have been highlighted. It can be noticed that, in the first case, the robot interrupts the human in the performance of its activity.

Table IV shows the results of navigation with and without *Space Affordances*, obtained for each of the metrics used: average minimum distance to a human during navigation, d_{min}; distance traveled, d_t; navigation time, τ; cumulative heading changes, CHC and personal space intrusions, Ψ. It is also indicated whether the activity performed by the human has been interrupted or not.

VI. Conclusions and Future Works

This article presents an extension of an algorithm for planning socially-accepted paths in human environments. The algorithm is based on the well-known Djiskstra's algorithm, where the original free space graph is modified according to the social interaction spaces. This article takes into account the personal spaces in an interaction between people, and also the spaces between people and the objects with which they interact. The metrics used to validate the proposal demonstrate that the planned paths have a socially-accepted behavior.

Although the results demonstrate the validity of the proposal, in future works the use of a real robot and questionnaires is considered in order to gather information on the acceptability of the planned paths.

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